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Assessing drivers of CO_2 emissions in China's electricity sector: A metafrontier production-theoretical decomposition analysis

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ABSTRACT

Abating CO_2 emissions from the electricity sector in China has received increasing attention in the past years. Assessing the drivers behind CO_2 emissions is fundamental to identifying cost-effective policy measures to reduce emissions. Production-theoretical decomposition analysis (PDA) has been applied for such a purpose owing to its strength in quantifying the impacts of efficiency and technology related factors. As the determinants of emissions are likely to be affected by the group heterogeneity, we develop a metafrontier PDA (MPDA) model to resolve the heterogeneity issue. Applying the proposed MPDA model to examine the change in CO_2 emissions from 93 Chinese fossil fuel power plants during 2005 and 2010 shows that all technology-related effects reduced power plants' emissions, but at varying degrees. While the emission efficiency improvement was the primary contributor to the emission abatement in the 93 plants, the group heterogeneity had exerted an influence on emissions, and the change in the heterogeneity slightly reduced the emissions. More detailed results with further discussions are presented.

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1. Introduction

Abating energy-related carbon dioxide (CO_2) emissions has attracted global attention given the role of CO_2 in climate change. As the largest CO_2 emitter across the world since 2006, China has been facing severe environmental and political pressures. Of major energy-consuming sectors, the electricity sector has been the primary source of CO_2 emissions in China (IEA, 2015a). Fig. 1 shows that electricity generation in China expanded from 1387 terawatt hours (TWh) in 2000 to 5706 TWh in 2014. Despite the increasing use of renewable energy during the past years, fossil fuel, particularly coal, comprised 75% of the overall energy consumption in China's electricity sector in 2014. The huge need of electricity together with the dominant share of fossil fuel in electricity production led to immense CO_2 emissions. With the potential economic growth and further urbanization and electrification in China, the need of electricity, as well as the CO_2 emissions caused by the sector, are projected to be substantial, particularly in the near future (IEA, 2015b).

Policy measures have been carried out at various levels to reduce emissions from electricity production in China. At the country/provincial level, governments usually play the leading role. For example, the Chinese government has set binding goals of energy conservation and emissions abatement for the electricity sector since its 11th Five-year plan (FYP) commencing 2006. Going a step further to the sectoral level, individual power plants have deeply involved in the course of emission abatement through the carbon market. Pilot carbon market was launched in seven Chinese provinces in 2013, and the electricity sector is one of the sectors that were first included in the carbon market and under stringent regulation. In the recently launched national emissions trading system (ETS) in December 2017, only the electricity sector is covered. These developments stress the importance of the electricity sector in emission abatement in China. Within the ETS framework, power plants are first granted emissions allowances, and will be charged for more quota if their emissions exceed the initial allowances. Constrained by the trading system, power plants' stakeholders are economically incentivized to reduce emissions. Consequently, a pivotal question is to identify cost-effective measures to mitigate emissions, which is grounded largely on understanding the driving forces behind emissions of the power sector. This is the objective of this study.

In the literature, a popular approach to assessing the drivers of changes in emissions is decomposition analysis. Decomposition

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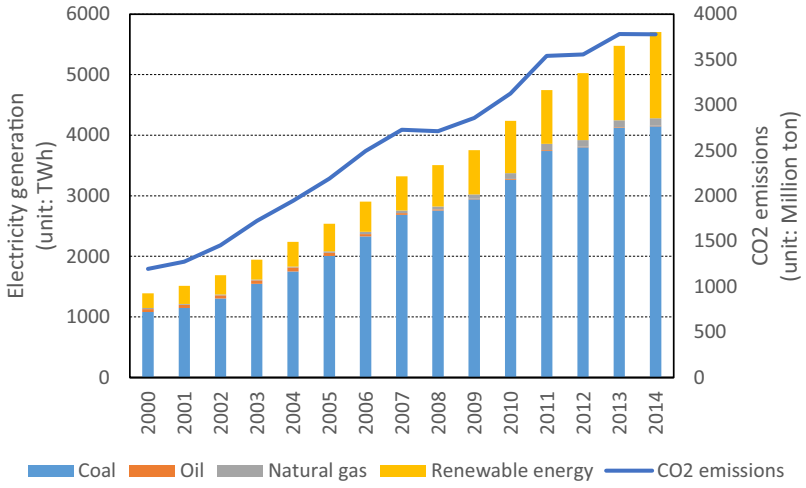

Fig. 1. China's electricity generation by source and CO_2 emissions from power sector, 2000–2014 (Data source: IEA world energy balance).

analysis is an accounting approach that can distribute a change in an aggregate indicator to a set of predefined factors. Three branches of decomposition analysis, namely index decomposition analysis (IDA), structural decomposition analysis (SDA) and production-theoretical decomposition analysis (PDA), have been proposed. From an energy systems perspective, the most basic form of IDA examines the energy and/or emission performance of an entity in three aspects, namely activity intensity, activity structure and total activity level. Built upon the input-output tables, SDA is able to model an overall economic system and investigate the impacts of economic production structure and final demand. A review of recent IDA and SDA studies is given in Wang, Ang, and Su (2017a).

Different from IDA and SDA, PDA is established within a production theory framework that is based on production economics. General production processes, i.e. using multiple inputs to produce multiple outputs as well as pollutants, can be modelled using the non-parametric frontier approach, i.e. data envelopment analysis (DEA), and the technical efficiency of production units can be estimated with respect to the best practice frontier within the total-factor framework. Examples of DEA studies examining the technical efficiency of the electricity sector include Cook and Zhu (2007), Wang, Wei, and Huang (2017), and Korhonen and Luptacik (2004).[1] The results generated by DEA models are useful to comparing generation units in terms of efficiency and tracking the productivity change of generation units. However, the impacts of efficiency and productivity change on emissions are omitted in these analyses. The PDA technique fills up this gap by incorporating technical efficiency measures into decomposition analysis.[2] From the production systems viewpoint, the total-factor framework allows PDA to offer economic insights regarding the drivers behind changes of emissions from efficiency and technology points of view (Zaim, Uygurtürk Gazel, & Akkemik, 2017). This is the main advantage of PDA over IDA and SDA (Wang, Ang, & Zhou, 2018). PDA analysis is therefore suitable for pinpointing directions to reduce emissions at the sectoral and micro levels. Given the objective of this study, we opt for the PDA technique.

PDA has experienced methodological progress in the past years. Pasurka (2006) first devises a PDA model to examine NO_x and SO_2 emissions of the United States' power plants, and shows that the technical efficiency improvement contributed to the emissions reduction while the technological change drove up the emissions. Within a non-parametric frontier framework, Zhou and Ang (2008) formalize the PDA approach to analyze aggregate CO_2 emissions. Later on more improvements have been made to the PDA methodology. For example, Zhang, Tan, Tan, and Yuan (2012) introduce the efficiency measurements for multiple inputs/outputs to the PDA literature, Wang (2013) studies the substitution effects among inputs using PDA, and Wang et al. (2018) resolve the sectoral and regional heterogeneities in the PDA modelling. The PDA technique has been applied to study energy consumption and CO_2 emissions at both the economy-wide and sectoral levels. While there are a number of economy-wide PDA studies, e.g., Kim and Kim (2012) and Zhang et al. (2012), application of PDA at the sectoral level is still at an early stage and the only two examples are Pasurka (2006) and Liu, Zhou, Zhou, and Wang (2017).

Determinants of emissions are affected by the heterogeneities among production entities in the patterns of energy use and emissions. At the sectoral level, group heterogeneity has been found important in assessing the efficiency and productivity of entities.[3] A reason is that entities usually possess varying production elements, exhibit different production technology levels and operate in different production environments (O'Donnell, Prasada Rao, & Battese, 2008). Taking the electricity sector as an example, power plants of different countries are often characterized by diverse generation technologies and fuel mixes which depend on the development stages and resource endowments of countries. For a particular country, power plants of different ownerships may be operated at varying management and regulation levels. All these issues lead to that groups of power plants operate with different production technologies in different environments. The group heterogeneity in the electricity sector has been widely observed in a number of countries, e.g., India (Murty, Kumar, & Dhavala, 2007), China (Zhang & Choi, 2013) and Germany (Seifert, Cullmann, & von Hirschhausen, 2016). Ignoring the group heterogeneity masks the varying performance of power plants in different groups, and therefore results in biased estimation of driving forces

[1] Refer to Gonzalez, Zhu, Zanoni, and Maculan (2017), Zhou, Yang, Chen, and Zhu (2018), and Zhou, Ang, and Poh (2008) for excellent reviews of DEA analysis in energy and environmental studies.

[2] In addition to analyzing changes in emissions and energy consumption, the decomposition technique has also been used in quantifying the determinants of technical efficiency and productivity in frontier studies. See, for example, Kao (2016) and Lee and Johnson (2012) that deal with efficiency decomposition, and Kao (2017) that studies the decomposition of Malmquist productivity index.

[3] As a note, regions and sectors are usually found heterogeneous in economy-wide energy use and emissions, and the sectoral and regional heterogeneities in emissions have been observed for a wide range of economies, including China (Wang & Zhou, 2018a; Wang, Ang, Wang, & Zhou, 2017).

behind emissions of power sector. However, no PDA study that deals with the group heterogeneity has so far been reported.

Given the above, this study aims to fill the gap by assessing the drivers of CO_2 emissions in China's electricity sector while accounting for the group heterogeneity. To this end, we first develop a refined PDA approach on the basis of the metafrontier technique, which is widely used to examine group heterogeneity in the frontier analysis. The proposed metafrontier PDA model decomposes a change in emissions of power plants into six effects, including the impacts of emission efficiency, technological change and technology gap, and the last one captures the influence of group heterogeneity on entities' emissions. To demonstrate the proposed approach, we apply the metafrontier PDA model to empirically study 93 Chinese fossil-fueled power plants' CO_2 emissions changes during the 11th five-year plan period (2005–2010) of China. The empirical results reveal that while the emission efficiency improvement was the primary contributor to emissions abatement for the 93 plants, the group heterogeneity had exerted an influence on emissions, and the change in the heterogeneity slightly reduced the emissions. Results at the aggregate and group levels are reported, which are expected to be useful for stakeholders to pinpoint directions for further emissions abatement in the electricity sector of China.

The rest of the paper is organized as follows. Section 2 introduces the methodologies. Section 3 describes the data, and Section 4 presents the results with discussions. Section 5 concludes.

2. Methodology

2.1. Environmental production technology

Suppose N $(i = 1, ..., N)$ power plants, which can also be called decision making units (DMUs), are under evaluation. Each plant uses fuel input (F_i) and non-energy inputs to generate electricity (E_i). Here we use the number of employees (L_i) and the installed generation capacity (G_i) of power plants to represent the non-energy inputs.[4] Environmental pollutions, including CO_2, SO_2 and NO_x, are simultaneously generated as by-products. Given the purpose of this study, we use CO_2 emissions (C_i) as a representation of the undesirable outputs. Within the production theory framework, we can use the production possibility set to characterize the production technology for the N entities as follows:

$$T = \{(F, L, G, E, C) : (F, L, G) \text{ can produce } (E, C)\} \tag{1}$$

Real production processes usually exhibit two common features. First, the undesirable output cannot be eliminated unless the production processes completely stop. Second, the abatement of undesirable output is not free, which always comes at a price. To reflect these two characteristics, we follow Färe, Grosskopf, Lovell, and Pasurka (1989) and impose two assumptions on the conceptual model in Eq. (1):

i. Null-jointness assumption: if $(F, L, G, E, C) \in T$ and $C = 0$, then $E = 0$.
ii. Weakly disposable assumption: if $(F, L, G, E, C) \in T$ and $0 \le \theta \le 1$, then $(F, L, G, \theta E, \theta C) \in T$.

With these two assumptions, Eq. (1) is able to reasonably represent the joint production of desirable and undesirable outputs, which is therefore known as the environmental production technology (Färe, Grosskopf, & Hernandez-Sancho, 2004). By adopting the non-parametric frontier approach, the environmental production technology exhibiting constant returns to scale (CRS) is modelled as follows:[5]

$$T = \Big\{(F, L, G, E, C) : \sum_i \lambda_i F_i \le F,\ \sum_i \lambda_i L_i \le L,\ \sum_i \lambda_i G_i \le G,\ \sum_i \lambda_i E_i \ge E,\ \sum_i \lambda_i C_i = C,\ \lambda_i \ge 0, i = 1, ..., N\Big\} \tag{2}$$

where λ terms the intensity variable. Eq. (2) represents the most efficient joint-production level given the N observations.

2.2. Distance functions under metafrontier and group frontier

As discussed in the foregoing, group heterogeneity needs to be controlled since it is likely to exist in the general production processes and emission patterns at the sectoral level. The metafrontier concept introduced by Battese, Rao, and O'Donnell (2004) has been widely used in the frontier analysis to assess the technical efficiency of entities while accounting for the group heterogeneity, e.g. Fallah-Fini, Triantis, de la Garza, and Seaver (2012) and Walheer (2018). We follow and adopt the metafrontier approach to develop a refined PDA model to control the group heterogeneity.

Suppose that the N DMUs under investigation are heterogeneous in production environment. We can divide all the DMUs into groups, each of which consists of DMUs that share homogenous production environment. Assume that K $(l = 1, ..., K)$ groups are formed, and group l contains P^l $(u = 1, ..., P^l)$ entities. DMUs in one group may not be able to freely access other groups' technology, production elements and environmental constrains. Following the metafrontier approach, two types of production technology can be defined, namely the meta technology and the group-specific technology. The former envelops the production possibilities represented by all the N entities, while the latter covers only the observations in a particular group. Accordingly K group frontiers can be constructed.

By definition the meta technology is modelled as Eqs. (1) and (2). The production technology for group l is similarly modelled as:

$$T_l^g = \{(F_l, L_l, G_l, E_l, C_l) : (F_l, L_l, G_l) \text{ can produce } (E_l, C_l)\} \tag{3}$$

and further formulated by using the piece-wise linear equations as follows:

$$T_l^g = \Big\{(F_l, L_l, G_l, E_l, C_l) : \sum_j \lambda_j F_j \le F,\ \sum_j \lambda_j L_j \le L,\ \sum_j \lambda_j G_j \le G \tag{4}$$

[4] The two variables have often been used as non-energy inputs in PDA studies and frontier studies that deal with power plants. See, for example, Yang and Pollitt (2009) and Wei, Löschel, and Liu (2015).

[5] The CRS assumption has been widely adopted in modelling the generation processes of power plants. See, for example, Yang and Pollitt (2009) and Amado, Santos, and Sequeira (2013). Given the purpose of this study, we do not examine the impact of power plants' size, and follow the common practice to assume the constant returns to scale. If needed, other assumptions on the returns to scale, e.g. variable returns to scale (VRS), can be specified by modifying the constraints in Eq. (2).

$$\sum_j \lambda_j E_j \geq E$$
$$\sum_j \lambda_j C_j = C$$
$$\lambda_j \geq 0,\ j = 1, \ldots, P^l \Big\}$$

Compared to the meta technology, the group technology merely represents the best practice for a particular group of entities. It can be seen that the only difference between the meta technology and the group-specific technology in terms of modelling, i.e., Eqs. (2) and (4), is the coverage of observations that are used to construct the best practice frontier. The two types of technologies can then be used to benchmark entities with respect to different production technology levels, with a goal of capturing the impact of group heterogeneity.

On the basis of Eqs. (2) and (4), entities' emission performance can be quantified by employing a technical efficiency measure. In the literature, a number of efficiency measures have been proposed, e.g., the Russell measure (Russell, 1990), directional distance function (Färe & Grosskopf, 2000), slacks-based measure (Tone, 2001), and non-radial directional distance function (Zhou, Ang, & Wang, 2012). Of the commonly used efficiency measures, the non-radial additive measure has been considered desirable since it can exhaustively identify slacks in inputs/outputs under the weakly disposable assumption (Chen, 2013, 2014).[6] We hence follow Zhou et al. (2012) and respectively specify the efficiency models under the metafrontier and group frontier as follows:

$$\max \beta_o^m + \delta_o^m + \phi_o^m + \gamma_o^m + \theta_o^m$$
$$s.t. \begin{cases} \sum_i \lambda_i F_i \leq F_o - \beta_o^m \cdot F_o \\ \sum_i \lambda_i L_i \leq L_o - \delta_o^m \cdot L_o \\ \sum_i \lambda_i G_i \leq G_o - \phi_o^m \cdot G_o \\ \sum_i \lambda_i E_i \geq E_o + \gamma_o^m \cdot E_o \\ \sum_i \lambda_i C_i = C_o - \theta_o^m \cdot C_o \\ \lambda_i,\ \beta_o^m, \delta_o^m, \phi_o^m, \gamma_o^m \text{ and } \theta_o^m \text{ are nonnegative, } i = 1, \ldots, N \end{cases} \quad (5)$$

and

$$\max \beta_o^g + \delta_o^g + \phi_o^g + \gamma_o^g + \theta_o^g$$
$$s.t. \begin{cases} \sum_j \lambda_j F_j \leq F_o - \beta_o^g \cdot F_o \\ \sum_j \lambda_j L_j \leq L_o - \delta_o^g \cdot L_o \\ \sum_j \lambda_j G_j \leq G_o - \phi_o^g \cdot G_o \\ \sum_j \lambda_j E_j \geq E_o + \gamma_o^g \cdot E_o \\ \sum_j \lambda_j C_j = C_o - \theta_o^g \cdot C_o \\ \lambda_j,\ \beta_o^g, \delta_o^g, \phi_o^g, \gamma_o^g \text{ and } \theta_o^g \text{ are nonnegative, } j = 1, \ldots, P^l \end{cases} \quad (6)$$

where the subscript o denotes the entity under evaluation, superscript m denotes metafrontier, superscript g denotes group frontier, β, δ, ϕ, γ and θ denote the parameters for slacks in inputs/outputs. By maximizing all the slacks parameters, model (5) and model (6) are able to exhaustively explore the slacks in inputs/outputs.[7] The term $\theta_o^m \cdot C_o$ is the slacks for emissions of entity o with respect to the metafrontier, while $\theta_o^G \cdot C_o$ is the corresponding slacks under the group frontier. The slacks indicate entities' distance away from relevant best practice frontier in terms of emissions. A zero slacks implies that the entity is located on the best practice frontier.

Based on the slacks, emission-orientated distance function under the metafrontier and that under the group frontier can respectively be defined as:

$$D_{C,o}^m = \frac{1}{1-\theta_o^m} = \frac{1}{CE_o^m} \quad (7)$$

$$D_{C,o}^g = \frac{1}{1-\theta_o^g} = \frac{1}{CE_o^g} \quad (8)$$

where CE^m is the emission efficiency performance index with respect to the metafrontier, and CE^g is that under the group frontier. The nonnegative slacks lead to that these two distance functions are not less than unity. The items CE^m and CE^g are indications of entities' technical efficiency in emissions with respect to the metafrontier and the group frontier, respectively. It can be found that these two efficiency indexes are not larger than unity. An efficiency index equal to unity implies that the entity possesses the most efficient production level in terms of emissions with respect to the corresponding reference technology. O'Donnell et al. (2008) show that the technical efficiency under group frontier, i.e. CE^g, is not less than that under the metafrontier, i.e., CE^m. The reason is that the metafrontier envelops all observations and therefore all group frontiers, which implies that the meta technology is not less efficient than any group technologies. As a result, entities' emission slacks with respect to the metafrontier is not less than that under the group frontier, rendering $CE^m \leq CE^g$. The ratio between the meta technical efficiency index and the group technical efficiency index can be viewed as an indication of the technology gap, which is formulated as:

$$MTR_{C,o} = \frac{CE_o^m}{CE_o^g} \leq 1 \quad (9)$$

The term $MTR_{C,o}$ measures the emission abatement technology gap for the oth entity. A larger value of $MTR_{C,o}$ suggests a narrower gap between the group technology and the meta technology, and vice versa. For instance, if the technology gap between the metafrontier and the group frontier is narrow for a given entity, the technical efficiency values under the two frontiers are close, which results in that the technology gap ratio approaches unity.

2.3. Metafrontier PDA model

The aggregate emissions of the N power plants can be modelled as:

$$C_{agg} = \sum_i C_i = \sum_i \frac{C_i}{E_i} \cdot \frac{E_i}{E_{agg}} \cdot E_{agg} = \sum_i \frac{C_i}{E_i} \cdot S_i \cdot E_{agg} \quad (10)$$

where E_{agg} denotes the aggregate electricity generation by all the N power plants, C_i/E_i is the emission intensity of plant i, and $S_i = E_i/E_{agg}$ denotes the electricity generation structure in terms of power plants' output share. By incorporating the metafrontier distance functions defined in Eq. (7), emission intensity of plants can be split into two factors, i.e., $D_{C,i}^m$ and $C_i/(E_i \cdot D_{C,i}^m)$. The former measures the technical inefficiency in emissions of plant i, as discussed in the previous section. On the other hand, the latter can be interpreted as the potential emission intensity (PEI) of power plant i since the emissions is deflated by corresponding technical inefficiency (Zhou & Ang, 2008). PEI indicates the potential level of emission intensity for a plant if the plant's emission performance could be improved to the best practice under the meta technology

[6] The non-radial additive measure has been widely adopted in efficiency and productivity analysis. See, for example, Wang, Zhou, and Zhou (2013), Yang and Yang (2015) and D'Inverno, Carosi, Romano, and Guerrini (2017).

[7] As shown in Zhou, Ang, and Wang (2012), multiple optimal solutions occur for Eqs. (5) and (6) only when the objective function equals unity. We have checked the empirical results in the sections that follow, and no multiple optimal solution exists.

by excluding technical inefficiency. Accordingly Eq. (10) can be rewritten as:

$$C_{agg} = \sum_i C_i = \sum_i \frac{C_i / D^m_{C,i}}{E_i} \cdot D^m_{C,i} \cdot S_i \cdot E_{agg} \tag{11}$$

Suppose that the data in year t and year $t+1$ are available. By using the production technology in time period $t+1$ as the reference, we can model the arithmetic change in the aggregate emissions between year t and year $t+1$ as:

$$C^{t+1}_{agg} - C^t_{agg} = \sum_i \frac{C^{t+1}_i / D^{m,t+1}_{C,i}(t+1)}{E^{t+1}_i} \cdot D^{m,t+1}_{C,i}(t+1) \cdot S^{t+1}_i \cdot E^{t+1}_{agg} - \sum_i \frac{C^t_i / D^{m,t+1}_{C,i}(t)}{E^t_i} \cdot D^{m,t+1}_{C,i}(t) \cdot S^t_i \cdot E^t_{agg} \tag{12}$$

Alternatively, the change in the aggregate emissions can be similarly modelled by using the reference technology in year t. To avoid arbitrary selection of the period for reference technology, we follow Zhou and Ang (2008) and use the geometric mean of distance functions under production technology in year t and year $t+1$ to deflate emissions. Eq. (12) is accordingly re-specified as[8]:

$$\begin{aligned} C^{t+1}_{agg} - C^t_{agg} &= \sum_i PEI^{t+1}_i \cdot \left(D^{m,t+1}_{C,i}(t+1) \cdot D^{m,t}_{C,i}(t+1)\right)^{1/2} \cdot S^{t+1}_i \cdot E^{t+1}_{agg} \\ &\quad - \sum_i PEI^t_i \cdot \left(D^{m,t+1}_{C,i}(t) \cdot D^{m,t}_{C,i}(t)\right)^{1/2} \cdot S^t_i \cdot E^t_{agg} \\ &= \Delta C_{pei} + \Delta C_{mep} + \Delta C_{str} + \Delta C_{act} \end{aligned} \tag{13}$$

where Δ denotes the additive effects, and $PEI^{t+1}_i = [C^{t+1}_i / (D^{m,t+1}_{C,i}(t+1) \cdot D^{m,t}_{C,i}(t+1))^{1/2}] / E^{t+1}_i$.[9] The term PEI^t_i is defined similarly. It is shown that a change in the aggregate emissions is attributable to four factors, i.e., PEI of plants, emission performance of plants, generation structure and the total electricity generation, whose impacts are given in the last line of Eq. (13). The potential emission intensity effect (ΔC_{pei}) captures non-technical effects on emissions since the technical inefficiency that is represented by distance functions has been isolated. The meta emission performance effect (ΔC_{mep}) quantifies the overall impact of technical performance on emissions. The generation structure effect (ΔC_{str}) reflects the impact of the electricity generation structure change on emissions, while the total electricity generation change (ΔC_{act}) measures the impact of overall output. A positive effect indicates that the change in the factor drives up the aggregate emissions between year t and year $t+1$, and vice versa. For instance, an improvement in entities' potential emission intensity during year t and year $t+1$ (i.e. $PEI^{t+1} < PEI^t$) results in a negative effect (i.e. $\Delta C_{pei} < 0$), which implies that the change in PEI contributes to reduce the aggregate emissions during this time period.

Wang et al. (2018) point out that the calculation of decomposition effects in Eq. (13) is essentially an index number problem since the disaggregation, i.e., entity i, is involved. A specific decomposition method is needed to compute these effects. Of commonly used decomposition methods in the literature, LMDI-I has been the most popular one as it possesses several desirable properties (Ang, 2015; Ang & Wang, 2015). We apply LMDI-I to calculate the four decomposition effects in Eq. (13) as follows:

$$\Delta C_{pei} = \sum_i w_i \ln PEI^{t+1}_i / PEI^t_i \tag{14}$$

$$\Delta C_{mep} = \sum_i w_i \ln \frac{\left(D^{m,t+1}_{C,i}(t+1) \cdot D^{m,t}_{C,i}(t+1)\right)^{1/2}}{\left(D^{m,t+1}_{C,i}(t) \cdot D^{m,t}_{C,i}(t)\right)^{1/2}} \tag{15}$$

$$\Delta C_{str} = \sum_i w_i \ln S^{t+1}_i / S^t_i \tag{16}$$

$$\Delta C_{act} = \sum_i w_i \ln E^{t+1}_{agg} / E^t_{agg} \tag{17}$$

where $w_i = L(C^{t+1}_i, C^t_i)$ is the weight function in LMDI-I, and $L(\cdot,\cdot)$ is the logarithmic mean function given by

$$L(a,b) = \begin{cases} \dfrac{a-b}{\ln a - \ln b}, \text{ if } a \neq b \\ a, \text{ if } a = b \end{cases}$$

The emission performance effect given by ΔC_{mep} in Eq. (15) captures the impact of entities' emission productivity change with respect to the metafrontier since the logarithmic item is the reciprocal of a meta Malmquist productivity index.[10] Using the relationship given in Eqs. (7)–(9), the meta emission productivity change effect can be expanded as:

$$\begin{aligned} \Delta C_{mep} &= \sum_i w_i \ln \frac{\left(D^{m,t+1}_{C,i}(t+1) \cdot D^{m,t}_{C,i}(t+1)\right)^{1/2}}{\left(D^{m,t+1}_{C,i}(t) \cdot D^{m,t}_{C,i}(t)\right)^{1/2}} = \sum_i w_i \ln \frac{CE^{g,t}_i}{CE^{g,t+1}_i} \\ &\quad + \sum_i w_i \ln \frac{\left(D^{g,t}_{C,i}(t) \cdot D^{g,t}_{C,i}(t+1)\right)^{1/2}}{\left(D^{g,t+1}_{C,i}(t) \cdot D^{g,t+1}_{C,i}(t+1)\right)^{1/2}} \\ &\quad + \sum_i w_i \ln \frac{\left(MTR^{t+1}_{C,i}(t) \cdot MTR^t_{C,i}(t)\right)^{1/2}}{\left(MTR^{t+1}_{C,i}(t+1) \cdot MTR^t_{C,i}(t+1)\right)^{1/2}} \\ &= \Delta C_{gec} + \Delta C_{gtc} + \Delta C_{tg} \end{aligned} \tag{18}$$

where the subscript *gec* denotes the impact of technical efficiency change within groups, *gtc* denotes the group technological change between year t and $t+1$, and *tg* denotes the effect of technology gap change. As such, the meta emission performance effect (ΔC_{mep}) can be further explained by the three effects in Eq. (18). The first item on the right hand side (RHS) of Eq. (18), i.e., $\sum_i w_i \ln CE^{g,t}_i / CE^{g,t+1}_i$, captures the impact of entities' group technical efficiency change during year t and year $t+1$. The second item on the RHS of Eq. (18) reflects the effect of shrinkage or expansion of the group best practice frontier, while the third item measures the impact of technology gap change on the aggregate emissions. Substituting Eq. (18) in Eq. (13) yields the eventual decomposition of the aggregate emissions, which is given as:

$$C^{t+1}_{agg} - C^t_{agg} = \Delta C_{pei} + \Delta C_{gec} + \Delta C_{gtc} + \Delta C_{tg} + \Delta C_{str} + \Delta C_{act} \tag{19}$$

[8] In addition to the additive decomposition of the arithmetic change in the aggregate emissions, the ratio change in the emissions can be similarly decomposed using the multiplicative decomposition, which is given in Appendix A.

[9] Mixed-period linear programming problems, e.g., $D^{m,t}_{C,i}(t+1)$, are involved here. Infeasible solutions may occur in solving the mixed-period problems. As documented in Wang, Chiu, and Chiu (2015), a common practice to deal with the infeasible solutions is to treat corresponding observations as they are located on the frontier. We follow this strategy in this study, which may nonetheless cause limitations in interpreting the numerical results.

[10] It should be noted that our definition of the meta productivity index is different from the productivity index that has widely been used in the metafrontier studies, which is usually defined on the basis of the global frontier that envelops all observations in all time periods, e.g. year 0, 1,..., T (Zhang & Choi, 2013). An underlying assumption behind the global frontier is that entities in any period can access production technologies in all other periods, which may not be valid in the present study. Besides, the global productivity index is dependent heavily on the dataset used in a study. For example, the estimation of productivity change from year 0 to year 1 is likely to be affected if we add one more year (say, year T+1) to the overall dataset or drop some years' data (say, year T). This fact may render the global productivity index vulnerable in some cases. While fully acknowledging the merits of the global productivity index, we deem that the meta productivity index given in Eq. (15) is more suitable in the current context since it can overcome the two problems mentioned above.

Eq. (19) will be referred to as the metafrontier PDA (MPDA hereafter) model. The change in the aggregate emissions are decomposed into six effects, three of which are related to production technology. The impacts of technical efficiency (ΔC_{gec}) and technological change (ΔC_{gtc}) are evaluated within individual group containing entities that are homogenous in production environment. The group heterogeneity is further revealed as the gap between group frontier and metafrontier, whose impact on the aggregate emissions is quantified as ΔC_{tg}. These three effects together explain the impact of entities' technical performance on the aggregate emissions. Besides, the potential emission intensity effect (ΔC_{pei}) captures the impacts of non-emission-technology factors that affect the production processes, e.g. fuel quality and mix, technical inefficiency in outputs, etc. At the aggregate level, the generation structure effect quantifies the impact of desirable output structure change, and the total generation effect indicates the impact of overall output change for the N entities. At the entity level, the sum of the two effects (i.e. $\Delta C_{str} + \Delta C_{act}$) yields the impact of individual entities' output change.

The proposed MPDA model has some advantages over the existing decomposition analysis techniques. Compared to IDA, the strength of the MPDA model lies in further analyzing the impacts of production technology related factors.[11] As shown in Appendix B, the MPDA model expands the emission intensity factor (C_i/E_i) in the IDA model by taking into account the efficiency performance, technological change and technology gap. These production technology related factors help policymakers to scrutinize emissions changes from a production systems viewpoint, and identify plausible directions regarding the management and technology aspects in the production side to reduce emissions. Compared to the existing PDA methodologies, a main advantage of the MPDA model is the quantification of the impacts of emission efficiency and technological change while accounting for the group heterogeneity. The emission efficiency change effect (ΔC_{gec}) and technological change effect (ΔC_{gtc}) allow entities to evaluate the impacts of their emission technologies with respect to the group best practice. The results are expected to point out directions to reduce emissions since learning from homogenous entities is more feasible and manageable. The technology gap effect (ΔC_{tg}) further informs decision makers about the impacts of group heterogeneities between individual groups and the entire set of entities, which might reveal possible directions for technological developments of groups. Overall these results enable decision makers to assess changes in entities' emissions in a more precise way by taking the group heterogeneity into consideration.

3. Data

We collect the data for 93 fossil-fueled power plants during China's 11th five-year plan period (2005-2010).[12] The 93 power plants accounted for 25% of China's thermal power generation, and 24% of total CO_2 emissions from the electricity sector, in 2010. As discussed in the previous sections, production units usually operate in different production environments. Eq. (1) shows that the general production is characterized and affected by multiple inputs, multiple outputs and the overall transformation process, i.e., the total-factor production framework. A number of factors in economic, environmental, management and technological aspects may result in heterogeneities between groups of power plants in terms of production environment. For instance, power plants may differ in substitutions between inputs, specific generation technologies, management systems and possible extra treatments on emissions, and may face environmental regulations at different degree. All these differences lead power plants to exhibit varying technology levels. In the literature, several criterion, e.g., fuel type (Seifert et al., 2016) and ownership (Zhang & Choi, 2013), have been used to category power plants into homogenous groups. Taking the ownership criteria as an example, Chinese power plants under different ownerships receive different subsidies, operate in different market conditions and face different environmental regulations. It is found that plants with the same ownership (e.g. public versus private) are more likely to be managed within homogenous production environment (Färe, Grosskopf, & Logan, 1985; Yang & Pollitt, 2010). As a result, ownership can be viewed as an indication of the production environment and the general production technology of power plants (Du, Hanley, & Zhang, 2016). We follow this principle and group the power plants in our dataset by ownership.[13]

China's power plants can be classified into two general categories by ownership, namely the state-owned plants and the local plants. The former is directly supervised by the *State Asset Supervision and Administration Commission* (SASAC), while the latter comprises of private plants, plants invested by foreigners or owned by local governments. In our dataset, 34 plants are local, and the remaining 59 plants are state-owned, which are run by seven enterprises.[14] The grouping details and summary statistics of inputs/outputs by the state-owned group and local group are given in Table 1. The descriptive statistics indicate that China's electricity sector is characterized by large-scale generation groups. It is also shown that the two groups display considerable variations in inputs/outputs, which might be an indication of the group heterogeneity in electricity production. CO_2 emissions from the 93 plants increased from 701 million tons (Mt) in 2005 to 756.2 Mt in 2010. Next we apply the MPDA model to examine the arithmetic change in the 93 power plants' emissions between 2005 and 2010, i.e., $C_{agg}^{2010} - C_{agg}^{2005} = 55.2$ Mt.

4. Results and discussion

As shown in Section 2, the distance functions for emissions need to be first calculated before conducting the decomposition analysis. Since the DEA estimation relies on a finite number of observations, the estimation results may be sensitive to the data sample used and the inputs/outputs selected, which raises uncertainties in the results. To examine the reliability of the results, we

[11] Here we only compare the MPDA model with IDA. The reason is that SDA is often confined to the economy-wide analysis since the input-output tables are used (Wang, Ang, & Su, 2017a, 2017b). Interested readers may refer to Wang, Ang, and Zhou (2018) for a comparison between PDA and SDA when applied at the economy-wide level.

[12] The data are sourced from the Compilation of Power Industry Statistical Data, China Electric Power Yearbooks, Chinese Industrial Enterprises Database and China Electric Power Industry Statistical Analysis in various years. All the data used in the empirical study are available upon request to the corresponding authors.

[13] It should be noted that different criterion would give rise to varying numerical results with different implications, even applied to the same dataset. For instance, grouping the power plants by technical characteristics, e.g., the specific technology used by generation units and the type of fuel inputs, may yield results that are more practically useful to plants' managers. Given the purpose of this study and constrained by the data availability, however, we choose the ownership of power plants as the single grouping criteria. This is a limitation of the present case study, and we elaborate on this issue as well as relevant caveats in Section 5.

[14] The seven major state-owned electricity generation enterprises are Huaneng Group (HN hereafter), Datang Corporation (DT), Huadian Corporation (HD), Guodian Corporation (GD), State Power Investment Corporation (SPIC), China Resources Power Holdings (CRPH) and Shenhua Guohua Electric Power (SH). Besides, there are two other major electricity generation groups, i.e., SDIC Power and China General Nuclear Power Group, whose energy source includes significant portion of renewable energy, e.g., hydropower and nuclear power. Since our objective is to analyze CO_2 emissions changes, we exclude these two enterprises in the present study.

Table 1
Grouping and summary statistics of the 93 power plants, 2005–2010.

Group	Number of plants	Statistics	Energy input (10^6 tce)	Installed capacity (GW)	Labor (person)	Electricity output (10^9 KWh)	CO_2 emissions (10^6 ton)
State-owned	59	Mean	2.72	1.59	1244.77	8.42	7.68
		Minimum	0.07	1.00	26	0.50	0.34
		Maximum	8.54	4.80	5550	26.60	24.23
		Standard deviation	1.14	0.67	899.20	3.48	3.18
Local	34	Mean	2.95	1.61	1215.31	9.25	8.40
		Minimum	1.44	1.00	42	4.40	3.99
		Maximum	7.11	4.20	2804	23.70	21.07
		Standard deviation	0.99	0.63	749.71	3.21	2.87

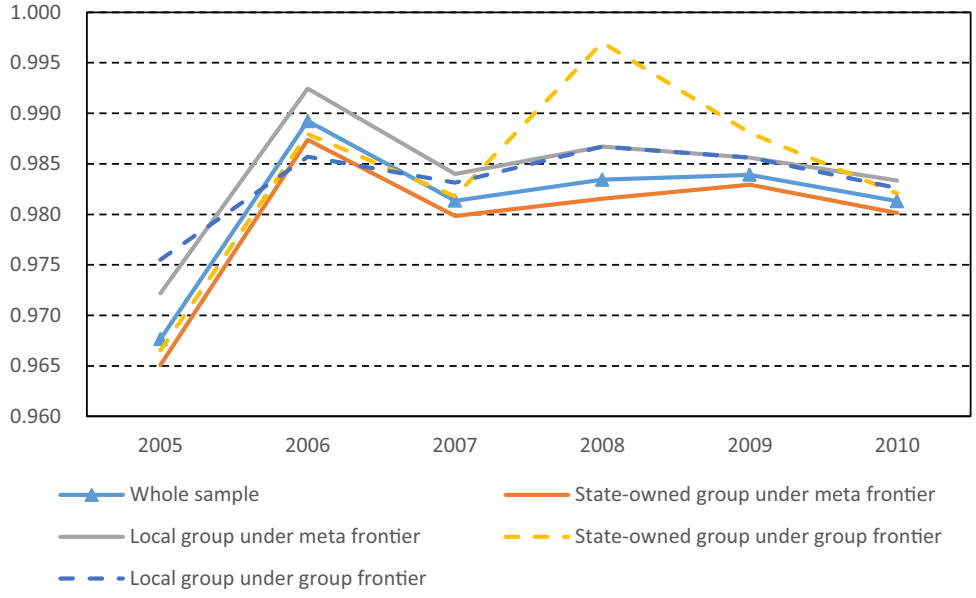

Fig. 2. Average emission efficiency performance of power plants under meta and group frontiers, 2005–2010.

perform a bootstrapping analysis (Simar & Wilson, 1998; Xie, Gao, Chen, & Deng, 2018).[15] The procedure of the bootstrapping analysis is briefly introduced in Appendix C. With the bootstrapping estimates of the distance functions, we compare it with the original estimates using the non-parametric Mann–Whitney test. The test results suggest that the original estimates have identical population distribution with the bootstrapping estimates, which indicates that the original estimates of the distance functions are reliable for further analysis. Fig. 2 shows that under the metafrontier, the local group had a higher emission efficiency performance than the state-owned group in all the six years. To examine the difference between the local group and the state-owned group in the emission efficiency, we apply the Mann–Whitney test again. The test results reject the null hypothesis of a common production technology for the two groups at the 0.05 significance level. This verifies that the group heterogeneity did exist between the local group and the state-owned group for the 93 power plants. Under the group frontier, Fig. 2 shows that the state-owned group had a relatively better emission efficiency performance than the local group, particularly in the latter period. The results are fairly different from those under the metafrontier, which implies that the estimation of emission efficiency is distorted without accounting for the group heterogeneity. Hence, the proposed MPDA model is necessary in the present context.

Applying the MPDA model introduced in Section 2.3 reveals the determinants of the change in emissions for the 93 power plants. Fig. 3 shows the decomposition results at the aggregate level. Unsurprisingly, the activity effect contributed the most to the increase in emissions between 2005 and 2010. The change in generation structure had relatively trivial effect on the total emissions change. The other four effects are found to decrease the emissions. Of these four effects, the efficiency improvement within groups was the top driving factor, followed by the potential emission intensity change and the group technological change. Fig. 4 further shows the changing pattern of driving forces between 2005 and 2010. It is observed that the emissions from the 93 plants continuously increased throughout the whole period except 2007/2008. The decline between 2007 and 2008 was possibly due to the global financial crisis taken place in 2008. The change in electricity output had always been the most significant cause of the growing emissions. Emission efficiency performance change is found to have had strong impact on emissions abatement in 2005/2006, which became weak in the later periods. As to the technological change within groups, it generally drove up the emissions in the first three years, and turned to reduce emissions in 2009 and 2010. The technology gap effect, which measures the impact of potential technology diffusion between groups, also saw a sign change from positive to negative during the period studied. The results coincide with the general technology development in the electricity sector of China.

Table 2 presents the decomposition results by the state-owned group and the local group. As aforementioned, the generation structure effect and total electricity output effect can be merged (i.e. $\Delta C_{str} + \Delta C_{act}$) to yield the group activity effect (i.e. ΔC_{gact}) at

[15] The bootstrapping method has been widely applied in the literature to examine the sensitivity and improve the accuracy of non-parametric frontier analysis results. See, for example, Aggelopoulos and Georgopoulos (2017) and Du, Worthington, and Zelenyuk (2018).

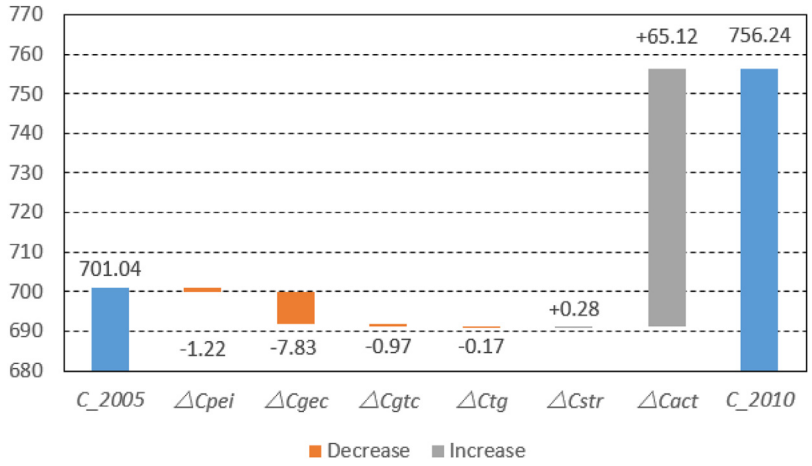

Fig. 3. Waterfall chart for the 93 power plants' emissions change, 2005–2010 (unit: million tons).

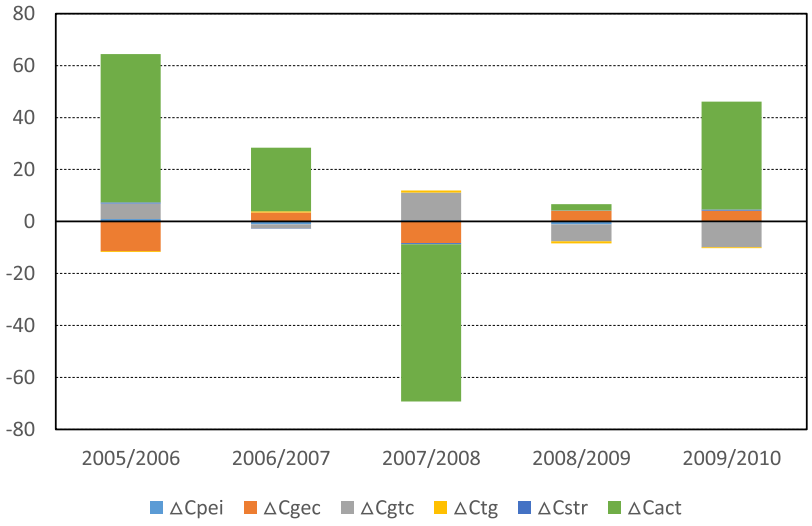

Fig. 4. Additive decomposition results at the aggregate level, 2005–2010 (unit: million tons).

Table 2
Additive decomposition results by groups (unit: million ton).

State-owned group						
Time period	△*Cpei*	△*Cgec*	△*Cgtc*	△*Ctg*	△*Cgact*	Total
2005/2006	1.23	−8.52	4.51	0.21	51.09	48.52
2006/2007	−0.77	2.68	−1.17	0.13	6.52	7.38
2007/2008	−0.26	−7.31	8.74	0.75	−35.66	−33.74
2008/2009	−0.27	3.92	−5.21	−0.93	1.69	−0.80
2009/2010	0.01	3.41	−6.91	−0.31	34.79	30.99
Cumulative	−0.07	−5.82	−0.05	−0.15	58.43	52.34
Local group						
Time period	△*Cpei*	△*Cgec*	△*Cgtc*	△*Ctg*	△*Cgact*	Total
2005/2006	−0.29	−2.85	1.46	−0.57	6.42	4.17
2006/2007	−0.37	0.75	−0.39	0.32	17.85	18.16
2007/2008	0.73	−0.95	1.98	0.03	−25.30	−23.50
2008/2009	−0.87	0.28	−1.33	0.24	0.80	−0.87
2009/2010	−0.35	0.75	−2.65	−0.04	7.20	4.90
Cumulative	−1.15	−2.02	−0.92	−0.01	6.97	2.86

the group/plant level, which quantifies the impacts of electricity output changes of groups and/or plants. It is shown that of the total 55.2 Mt increases in the 93 plants' emissions, 52.3 Mt were caused by the state-owned plants. The result reflects the dominant role of the state-owned generation groups in China's electricity sector, particularly after the nationwide action of shutting down small-size power plants since 2006. Similar patterns in the decomposition results for the state-owned group and local group are observed. For instance, the rising electricity output was the main factor driving up the total emissions for the two groups, while the emission efficiency performance change within group contributed the most to reduce emissions. Directly comparing the decomposition results given by the state-owned group and the local group may not be reasonable since the two groups consist of different numbers of plants and have different emission levels. Alternatively, Fig. 5 shows the additive decomposition results in percentage form by deflating the results with respect to the total emissions of respective group in 2005.[16] It is found that other than the group activity effect, the potential emission intensity effect together with the three technology-related effects had similar impacts for the state-owned group and local group. The four effects reduced the emissions of the 59 state-owned plants by 1.45%, while the corresponding estimate for the 34 local plants was 1.46%. However, Fig. 5 shows that the source of emissions reduction was different for the two groups. The technology gap shrinkage had larger effects for the state-owned plants on abating emissions, while the potential carbon intensity and technological change had larger effects for the local plants. The results suggest that plants in the state-owned

[16] Taking the activity effect of the state-owned group as an example, the corresponding estimate in percentage form is $\Delta C^S_{gact}/C^S_{2005} = 58.4/420 = 13.9\%$, as shown in Fig. 5.

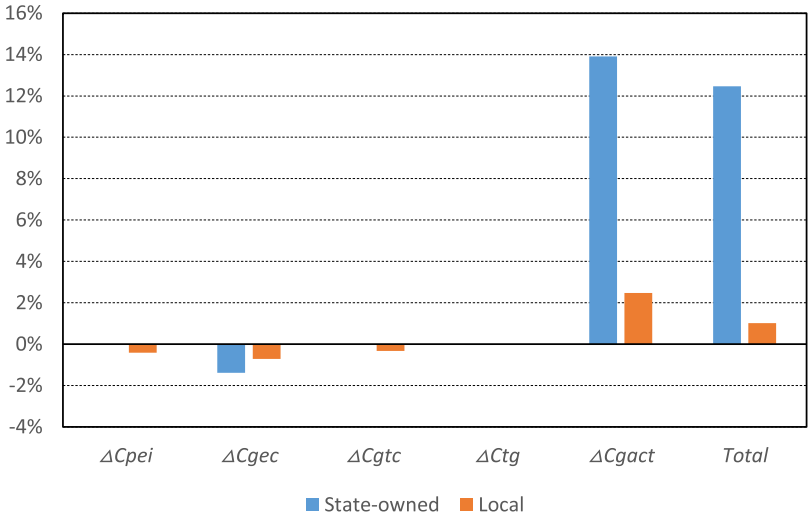

Fig. 5. Decomposition results by state-owned and local groups (effects are given in percentage).

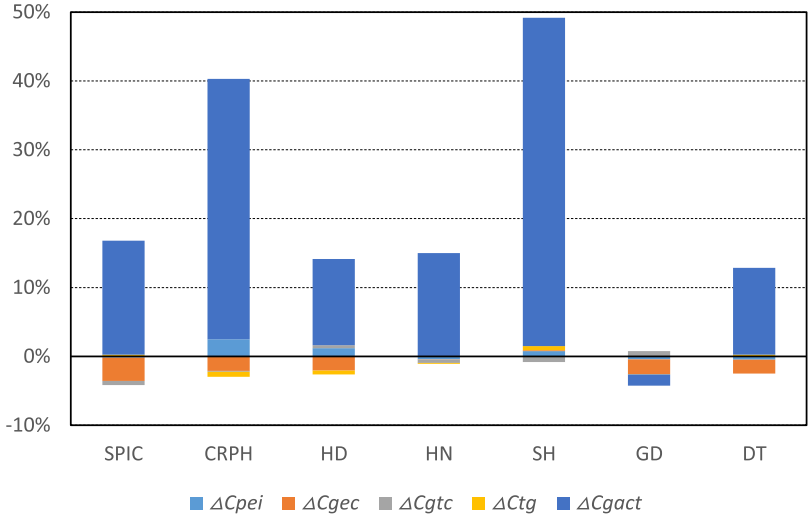

Fig. 6. Decomposition results by the seven state-owned generation groups (effects are given in percentage).

Table 3
Cumulative additive decomposition results by state-owned generation corporation, 2005–2010 (unit: million ton).

Generation corporation	No. of plants	$\Delta Cpei$	$\Delta Cgec$	$\Delta Cgtc$	ΔCtg	$\Delta Cgact$	Total
SPIC	2	−0.03	−0.53	−0.10	0.04	2.59	1.97
CRPH	3	0.45	−0.37	−0.02	−0.14	6.76	6.67
HD	8	0.60	−1.04	0.21	−0.27	6.28	5.78
HN	17	−0.47	−0.09	−0.63	−0.15	18.78	17.45
SH	4	0.21	0.04	−0.23	0.18	13.49	13.69
GD	12	−0.40	−1.88	0.68	−0.01	−1.45	−3.06
DT	13	−0.44	−1.94	0.04	0.20	11.98	9.85

group may further reduce emissions through stimulating emission technology improvement and enhancing the potential emission intensity. For plants in the local group, narrowing the technology gap with respect to the meta best practice may achieve considerable emission abatement potential.

Table 3 summarizes the cumulative decomposition results of the seven state-owned generation corporations. It is found that Huaneng registered the most substantial growth in emissions, followed by the plants of Shenhua and Datang. At the lower end, only the plants of Guodian Corporation saw a decline in emissions between 2005 and 2010. The main reason was the shrinking electricity output of Guodian's plants that are covered in the dataset. It is shown that the emission efficiency performance improvement helped to reduce emissions for all the plants, except for the four plants of Shenhua group. Technological change in the plants of Guodian, Huadian and Datang drove up their emissions, which was opposite to the case for the other four groups. Moreover, after excluding the technical inefficiency, the change in potential emission intensity of the plants of CRPH, Huadian and Shenhua further raised emissions. Fig. 6 displays the additive results for the seven generation groups' plants in percentage form. It is shown that the group technical efficiency contributed the most to emission abatement in the plants of SPIC, while the plants of Shenhua benefited the most from the technological change.

In summary, the growth in emissions of the 93 power plants during 2005 and 2010 was driven mainly by the rising electricity

output, while the technology related effects, including the impact of group heterogeneity, contributed marginally to emission mitigation. The overall development in emission abatement was not ideal as expected, particularly in view of the progress made by China in electricity generation technology in recent years. Further actions are clearly needed to reduce emissions from the electricity sector more effectively. Some implications can be drawn from our empirical results. First, it is necessary to continue enhancing production technology in the electricity sector. After shutting down small-size plants nationwide, the general technology level in China's electricity sector has improved. However, our empirical results show that the technology related effects were fairly limited during 2005 and 2010. The trivial impacts call for further efforts in improving technical efficiency performance and adopting cleaner technologies in the electricity sector. Second, narrowing the technology gap between the state-owned plants and the local plants can help to further abate emissions. The empirical results show that the two groups had heterogeneous technical efficiency effects and technological change effects on emissions. The technology gap changes for both groups helped to reduce emissions between 2005 and 2010, which was nevertheless at a fairly slight degree. It suggests that technology diffusion between plants in different groups may unveil considerable potential for emission mitigation in the electricity sector.

5. Conclusion

The objective of this study is to assess the drivers of CO_2 emissions from China's electricity sector while accounting for the group heterogeneity, and our contribution is primarily on the methodological front. Specifically, we propose a metafrontier PDA model that is able to account for the group heterogeneity among production units. On the basis of the metafrontier approach in the frontier analysis, we evaluate DMUs' emission performance with respect to both the group frontier and metafrontier, and further model the group heterogeneity as the gap between the technical efficiency under the two frontiers. The MPDA model specifies six effects to explain a change in emissions. In particular, emission technology related effects, i.e., the emission efficiency change effect, technological change effect and group heterogeneity effect, are captured. This is the main advantage of the MPDA model compared to the conventional PDA models and the other two decomposition techniques (i.e., IDA and SDA). The MPDA model can be flexibly applied to different pollutants at various disaggregation levels, including national/provincial, sectoral and firm levels. Results generated by the MPDA model help decision makers to understand the driving forces behind emissions changes with a focus on production technology, which could further lead to policy measures to reduce CO_2 emissions.

To demonstrate the proposed MPDA model, we empirically examine the change in CO_2 emissions of 93 Chinese thermal power plants between 2005 and 2010. The results show that the rising electricity output was the main cause of the emissions growth. On the other hand, changes in the potential emission intensity, emission efficiency performance, group technology and technology gap helped to reduce emissions. Of the four determinants, the emission efficiency performance change was the top contributor. The state-owned group and the local group differed significantly in the electricity generation performance, emissions and the underlying determinants. It is found that the technology gap shrinkage had larger effects for the state-owned plants on abating emissions, while the potential carbon intensity and technological change had larger effects for the local plants. Detailed results at the aggregate and group levels are reported, which may point out directions to abate emissions in China's electricity sector.

Inevitably there exist some limitations in this paper, and the primary issue is about the criteria used to group power plants in the case study. As discussed in the preceding, the difference in ownership can be viewed as an indication of the variations between power plants in production environment and production technology. This criteria is too broad to precisely capture the heterogeneity between power plants from an engineering perspective. Constrained by the data availability, however, we select the ownership of power plants (i.e. state-owned vs. local) as the single criteria in the present study. This limitation may introduce ambiguity in interpreting the impact of group heterogeneity on emissions, particularly for individual power plants. To derive actionable measures at the plant level, grouping criterion that better reflect technical characteristics of power plants should be adopted given that relevant data become available.[17]

The present study can be extended in a number of ways in the future. First, the dataset used in this study merely covers a minor portion of fossil-fueled power plants in China, which therefore cannot show the complete picture of the electricity generation groups. As such, the empirical results reported in this study apply to particular power plants in those giant generation groups. Analysis based on a complete dataset may yield results that are more representative and informative. Second, this study presents only temporal analysis of emissions changes in the electricity sector, i.e. emissions changes from one year to another. Comparisons of plants in terms of emission performance in a particular time period are lacking. Similar to Ang, Su, and Wang (2016) that apply the IDA technique and Wang and Zhou (2018b) that deal with spatial comparison, cross-sectional PDA analysis can be conducted to reveal the sources of differences between power plants in emission performance with a focus on production technology.

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Appendix A. Multiplicative MPDA model

With reference to Eq. (11) and similar to Eqs. (12) and (13), the ratio change in the aggregate emissions can be formulated as follows:

$$C_{agg}^{t+1}/C_{agg}^{t} = \frac{\sum_i PEI_i^{t+1}\cdot\left(D_{C,i}^{m,t+1}(t+1)\cdot D_{C,i}^{m,t}(t+1)\right)^{1/2}\cdot S_i^{t+1}\cdot E_{agg}^{t+1}}{\sum_i PEI_i^{t}\cdot\left(D_{C,i}^{m,t+1}(t)\cdot D_{C,i}^{m,t}(t)\right)^{1/2}\cdot S_i^{t}\cdot E_{agg}^{t}} = D_{pei}\cdot D_{mep}\cdot D_{str}\cdot D_{act} \quad (A.1)$$

where D denotes the multiplicative effects. Applying the multiplicative version of LMDI-I to Eq. (A.1) yields

$$D_{pei} = \exp\left(\sum_i w_i^{*}\ln PEI_i^{t+1}/PEI_i^{t}\right) \quad (A.2)$$

$$D_{mep} = \exp\left(\sum_i w_i^{*}\ln\frac{\left(D_{C,i}^{m,t+1}(t+1)\cdot D_{C,i}^{m,t}(t+1)\right)^{1/2}}{\left(D_{C,i}^{m,t+1}(t)\cdot D_{C,i}^{m,t}(t)\right)^{1/2}}\right) \quad (A.3)$$

[17] We thank an anonymous reviewer for pointing this issue out.

$$D_{str} = \exp\left(\sum_i w_i^* \ln S_i^{t+1}/S_i^t\right) \tag{A.4}$$

$$D_{act} = \exp\left(\sum_i w_i^* \ln E_{agg}^{t+1}/E_{agg}^t\right) \tag{A.5}$$

where $w_i^* = L(C_i^{t+1}, C_i^t)/L(C_{agg}^{t+1}, C_{agg}^t)$. The further decomposition of the meta emission performance effect (D_{mep}) can be similarly conducted as Eqs. (18) and (19). For the multiplicative decomposition results, an effect larger than unity contributes to raise the aggregate emissions, and vice versa.

Appendix B. Brief description of IDA model

IDA aims to analyse energy consumption and emissions from an energy systems perspective (Wang et al., 2017a). Eq. (10) is essentially an IDA model for the aggregate CO_2 emissions of power plants. Following Eq. (10), the change in the aggregate emissions during time period t and $t+1$ can be decomposed as

$$C_{agg}^{t+1} - C_{agg}^t = \Delta C_{int} + \Delta C_{str} + \Delta C_{act} \tag{B.1}$$

where the subscript *int* denotes the intensity effect. All other notations are similarly defined as those in Section 2. A change in the aggregate emissions can then be explained by the three factors, i.e. activity intensity, generation structure and the overall activity level. Applying LMDI-I to Eq. (10) and Eq. (B.1) yields:

$$\Delta C_{int} = \sum_i w_i \ln I_i^{t+1}/I_i^t \tag{B.2}$$

where $I_i = C_i/E_i$. The other two effects in Eq. (B.1) are the same as those in Eqs. (16) and (17). It can be shown that $\Delta C_{int} = \Delta C_{pei} + \Delta C_{mep} = \Delta C_{pei} + \Delta C_{gec} + \Delta C_{gtc} + \Delta C_{tg}$. From the above it can be found that PDA is essentially an extension of IDA by further studying the impacts of technical efficiency performance and technological change in the production side, as stated in Wang et al. (2018).

Appendix C. Procedure for bootstrapping analysis

We adopt the bootstrapping measure to examine the robustness of the DEA estimation of the distance functions for emissions. The bootstrapping analysis can be conducted by the following steps:

(1) Apply model (5) to estimate the DEA efficiency for each DMU under the metafrontier;
(2) Employ the bootstrapping technique to generate a random sample of large number of DMUs to decrease efficiency deviations, and calculate the bias-corrected efficiency for each DMU under the metafrontier;
(3) Repeat steps (1) and (2) to provide a set of estimates under the group frontiers. Details can be seen in Duan, Guo, and Xie (2016) and Xie et al. (2018);
(4) Conduct the Mann–Whitney test to statistically examine the difference between the original estimates and the bootstrapping estimates.

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